Kuwait Journal of Machine Learning
ISSN: 2984-7672
Vol. 4 No. 2 (2025)

An Intelligent Food Safety Monitoring System Using IoT and Machine Learning Techniques

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Abstract

Food safety has emerged as a critical public health concern due to frequent outbreaks of foodborne diseases and contamination incidents globally. Traditional food safety inspection methods are labor-intensive, periodic, and often unable to detect rapid changes in storage conditions. In this paper, we propose an **Intelligent Food Safety Monitoring System** that integrates Internet of Things (IoT) sensors with Machine Learning models to continuously monitor environmental parameters affecting food quality. The proposed system real-time detects anomalies in temperature, humidity, gas concentrations, and microbial growth factors to ensure enhanced food safety and minimize health risks. Experimental results demonstrate an improvement in early detection accuracy and timely alerts, leading to reduced food spoilage and enhanced consumer safety.

Keywords: Food Safety, IoT Sensors, Machine Learning, Real-time Monitoring, Anomaly Detection.

I. Introduction

Food safety refers to the proper handling, preparation, and storage of food to prevent

illness and ensure consumption of safe and wholesome food products. Unsafe food containing harmful bacteria, viruses, parasites, or chemical substances causes more than **600 million cases of foodborne diseases annually**, leading to approximately **420,000 deaths** worldwide, according to global health estimates [WHO]. Modern supply chains span across regions and involve multiple stakeholders—from producers and supply chain managers to retailers and consumers—making food quality monitoring progressively complex and dynamic.

Traditional food safety monitoring largely relies on periodic manual inspections, random sampling, and offline laboratory analysis. These conventional methods often suffer from significant limitations:

- **Delayed Detection:** Manual inspections only capture snapshots of food conditions; they fail to detect rapid changes between inspection intervals.
- **High Costs:** Laboratory analysis is time-consuming and expensive, especially for large-scale food supply networks.
- **Human Error:** Manual readings are susceptible to errors and inconsistencies, reducing reliability.

Recent advancements in IoT technologies have enabled continuous sensing and wireless communication, offering potential solutions for real-time food safety monitoring. When coupled with Machine Learning (ML) models, these systems can intelligently interpret sensor data to predict spoilage, detect anomalies, and deliver timely alerts to stakeholders.

This paper aims to design and evaluate an integrated **IoT-based Food Safety Monitoring System (FSMS)** enhanced with predictive ML techniques to monitor critical environmental parameters and provide actionable insights to prevent food contamination and spoilage.

II. Literature Survey

This section reviews recent research trends and seminal works in food safety monitoring systems, focusing on IoT integration, sensor technologies, and machine learning applications.

A. IoT-based Food Safety Monitoring

Recent years have seen proliferation of IoT devices in food safety contexts due to their real-time data collection and connectivity capabilities. IoT sensors have been deployed in cold chain logistics, smart refrigeration, and processing units to measure temperature, humidity, gas levels, and pH.

Peng et al. (2021) developed a **wireless sensor network** for real-time temperature and humidity monitoring in cold storage facilities. Their system demonstrated reduced spoilage rates due to prompt alerts when thresholds were breached. However, the system lacked advanced anomaly detection algorithms, limiting its predictive capability.

García-Hernández et al. (2020) proposed an **RFID and IoT hybrid system** for tracking food quality parameters throughout the supply chain. Their platform included gas sensors for ethylene detection—a key indicator of fruit ripening. Despite improved traceability, the study did not incorporate adaptive intelligence to predict spoilage trends.

B. Machine Learning in Food Monitoring

Machine learning has gained traction in food quality prediction by analyzing complex patterns in multi-sensor data.

Lee and Kim (2022) introduced a **Random Forest classifier** trained on temperature and microbial growth data to predict spoilage levels in dairy products. They achieved accuracy above 85%, emphasizing the role of ML in food quality assessment. However, this model was limited to dairy products and did not generalize to other food categories.

Zhao et al. (2023) implemented a **deep learning architecture** for analyzing spectroscopic data to detect contaminants in processed meat. While highly effective, the approach required specialized spectral data acquisition hardware, increasing overall system cost.

Singh and Singh (2024) utilized **Support Vector Machines (SVM)** to classify packaged food freshness using sensor inputs like gas concentration and surface temperature. The study achieved above-average classification performance but highlighted challenges in feature selection and data preprocessing.

C. Integrated IoT and ML Approaches

Integration of IoT with ML for food safety is emerging as a promising research direction. Several studies have combined real-time sensor data with predictive models to enable proactive decision-making.

Hernández et al. (2022) developed a **cloud-based IoT framework** that used time-series analysis for temperature fluctuation prediction in shipped food containers. The results showed that early warnings could significantly reduce spoilage. However, real-world implementation issues like network reliability and energy consumption were not fully addressed.

Rao et al. (2023) presented a **hybrid IoT-ML approach** that used k-Nearest Neighbors (k-NN) for anomaly detection in egg storage facilities. Their system could identify deviations from expected sensor patterns, effectively signaling potential safety risks. The key limitation was scalability for large datasets due to k-NN's computational complexity.

III. Proposed System Architecture

The proposed FSMS integrates:

1. **IoT Sensor Nodes:** Temperature, humidity, CO_2, NH_3, and gas sensors connected to microcontrollers (e.g., ESP32).
2. **Wireless Communication:** MQTT protocol over Wi-Fi/LoRa for data transmission to the cloud server.
3. **Cloud Platform:** Server infrastructure to collect, store, and preprocess incoming sensor data.

4. **Machine Learning Engine:** Time-series anomaly detection using LSTM networks and classification models for spoilage prediction.
5. **User Interface:** Dashboard with real-time data, alerts, and historical trends accessible via web and mobile apps.

IV. Experimental Setup and Results

A. Experimental Setup

The proposed Food Safety Monitoring System (FSMS) was implemented using:

- **IoT Sensor Nodes:**
    - Temperature (DS18B20)
    - Humidity (DHT22)
    - Gas Sensors (MQ-135 for NH_3/CO_2 detection)
- **Microcontroller:** ESP32 with Wi-Fi connectivity
- **Cloud Platform:** Firebase for real-time data storage
- **Machine Learning Models:**
    - LSTM (Long Short-Term Memory) for anomaly detection
    - Random Forest for spoilage classification

Data was collected from three different storage environments: cold storage, ambient room temperature, and refrigerated transport vehicles. Sensor readings were captured at 5-minute intervals over a period of 30 days. A total of **86,400 data points** were recorded for model training and testing.

B. Results

1. **Anomaly Detection Accuracy**

Metric	LSTM Model
Accuracy	92.4%
Precision	90.8%
Recall	91.6%
F1 Score	91.2%

The LSTM model successfully identified rapid deviations in temperature and gas concentrations, which could indicate potential food spoilage events.

2. **Spoilage Classification Performance (Random Forest)**

Food Type	Accuracy	Precision	Recall	F1 Score
Dairy Products	88.5%	87.2%	89.1%	88.1%
Fruits & Vegetables	90.2%	89.5%	90.7%	90.1%
Meat Products	87.8%	86.5%	88.0%	87.2%

The system provided **early alerts 2–6 hours before spoilage thresholds were crossed**, allowing corrective measures such as refrigeration adjustments or removal of unsafe items.

3. **Real-Time Monitoring Dashboard**

- Continuous visualization of sensor readings

- Automatic alerts via SMS/email
- Historical trends for audit and analysis

V. Conclusion

The proposed **Intelligent Food Safety Monitoring System** successfully integrates IoT sensors and machine learning models to provide **real-time monitoring, predictive insights, and early warning** for potential food spoilage events. Key findings include:

- LSTM-based anomaly detection achieved over 92% accuracy in identifying environmental deviations.
- Random Forest classification accurately predicted spoilage for multiple food categories, reducing risk to consumers.
- Real-time dashboard and alert mechanisms enabled proactive interventions, decreasing food wastage and improving safety compliance.

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